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CORTICONIC NETWORKS FOR HIGHER-LEVEL PROCESSING

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Abstract

A set of equations seeking to model the way the cortex interacts with subcortical areas to produce certain higher-level brain functions is described. The equations are those of a network of parametrically coupled maps that incorporates salient properties of the cortex. Justifications for this approach and demonstration of its effectiveness for a parametrically coupled logistic map network (PCLMN) are presented. The PCLMN can self-organize under information driven adaptation, is capable of handling dynamic (spatio-temporal) input patterns, furnishes an enormous number of attractors for inputs to choose from, plus other intriguing features that can be used in the design of intelligent systems.

Introduction

It is generally agreed that brain tissue is the most complex self-organizing matter known in the universe. In particular this applies to the cortex and all subcortical centers like the thalamus and the hippocampus with which the cortex interacts to carry out higher-level brain functions such as perception, cognition, memory, language, control of complex motion, speech and perhaps even awareness and consciousness. Understanding and creating models of how the cortex carries out such operations and implementing them in suitable fast and efficient algorithms or hardware will have far reaching implications for science, technology and medicine with the most obvious being the formulation and testing of models of higher-level brain functions and the design of future machines with brain-like intelligence.

To create a system of equations that models the cortex in every small detail, i.e. to model the cortex/brain on the <u>microscopic</u> scale of neurons, synapses, dendrites, axons and the dynamics of linear and nonlinear membrane patches with their voltage and chemically activated ionic channels, would be a daunting task even with the computational resources available today or predicted for the future.

For this reason we developed a macroscopic approach to modeling the cortex that is based on combining the tools of nonlinear dynamics and information theory with known salient organizational and anatomical features of the cortex. [1],[2] This approach produced the following *cortical equations* that describe the evolution of the state vector $\overline{X}(n)=\{X_i(n), i=0,1,2,...N-1\}$ of a parametrically coupled logistic map network (PCLMN) and the dynamics of the coupling factors matrix $\overline{C}(m)$:

$$X_i(n+1)=\mu_i(n)X_i(n)(1-X_i(n)) \quad i=0,1,2....N-1 \tag{1}$$

$$\mu_i(n)=4\left(X_i^s\right)^{C_i^s} e^{-\alpha n}+\left(1-e^{-\alpha n}\right)\frac{1}{N_i}\sum_{j\varepsilon|N_i|} 4\left(X_j(n)\right)^{C_{ij}} \tag{2}$$

$$C_{ij}(m+1)=C_{ij}(m)(1+\Delta C_{ij}(m)) \tag{3}$$

$$\Delta C_{ij}(m)=\delta \tanh \beta I_{ij} \tag{4}$$

$$I_{ij}=H_i+H_j-2H_{ij} \tag{5}$$

Here for simplicity, a one-dimensional network topology of N parametrically coupled logistic maps is considered. $X_i(n)\varepsilon[0,1]$ is the state variable of the i-th processing element (map) in the network, n is discrete integer time, $\mu_i(n)\varepsilon[0,4]$ is the control parameter of the i-th map, $X_i^s(n)\varepsilon[0,1]$ is the extrinsic input to the i-th element of the network, N_i is the number of maps connected to the i-th map. This includes usually nearest-neighbor and self connection for which $N_i=3$. In the numerical simulations described below the nearest-neighbor connections are set with a probability of $p=0.5$ or 0.7. This *symmetry breaking* is needed to make the network

converge to input-specific attractors. The self-coupling however is set with a probability of unity. The quantity α is a positive real constant (typically 0.1) setting the rate at which control over the dynamics of the network is passed from the extrinsic input to internal feedback from the nearest neighbor maps including self-feedback, $C_i^s = 0.5$ and $C_{ij} \varepsilon [0, \infty]$ represents the coupling factor between the j-th and i-th map. Note the coupling factor in this formulation is not coupling strength, because $X_i(n)$ ranges between zero and 1, $C_{ij} = 0$ gives maximum coupling or excitation and $C_{ij} = \infty$ gives zero coupling or maximum inhibition for all values of X_i except $X_i = 1$; m is the updating index. Typically 100 iterations are needed before the values of the coupling factors are updated. The initial coupling factor $C_{ij}(0)$ of the network are selected randomly in a range where the initial dynamics of the network is disorganized so as to include elements that spawn chaotic orbits. Typically, values for both C_{ii} and C_{ij} are selected randomly and uniformly in the [0, 0.5] range. $\Delta C_{ij}(m)$ is the change made in C_{ij} typically every $n = 100$ iterations of the network, δ, and β are noncritical constants, typically $\delta = 5, \beta = 10$ for the examples shown here, controlling the rate of adaptation; $I_{ij}(m)$ is the normalized mutual information at the m-th adaptation associated with the orbits of the j-th and i-th map observed over the preceding 100 iterations, H_i and H_j are respectively the entropies of the i-th and the j-th orbit and H_{ij} is the normalized cross entropy. Note that equations (1)-(5) describe two rates of evolution in time, one is fast describing the evolution of $\overline{X}(n)$ and second is slow describing the punctuated evolution of $\overline{C}(m)$.

Self-adaptation of the network under the influence of few (three or four) distinct input (stimulus) patterns $\overline{X}^s(n)$ leads the elements of the coupling matrix $\overline{C}$ to converge to fixed values that do not change with the application of additional inputs. At this stage the self-organization of the network is complete.

Publications [1],[2] contain the arguments and rationale that led to these equations and the way they are used to self-organize a PCLMN incorporating salient and plausible features of cortical organization many of which are not found in current neural net and connectionist models.

It is also possible by modifying the formula for adaptation, that attractors of any single class or a mix of classes selected from fixed-point, period-m, or chaotic can be achieved. The modification would be

$$\Delta C_{ij} = \delta \tanh\left|\beta I_{ij} - \gamma\right| \tag{6}$$

where the choice of the real constant γ enables the components of $\overline{\mu}(n)$ to converge to values distributed in any desired part of the μ_i axis in the bifurcation diagram of the i-th logistic map.

Significant Properties Of The PCLMN

The adapted or self-organized PCLMN has several unique useful properties described in [1] and [2] that are not found in conventional neural net and connectionist models of cortical dynamics. The most intriguing of these is the immense number of stimulus-specific attractors an adapted (self-organized) PCLMN has. The number is astronomical being $N_a = L^N$ where N is the size of the network and L is the number of levels over which the analog valued state variable $X_i(n), i = 1,2...N$ of the i-th element in the network is measured or discerned. We have strong evidence supporting the validity of this property. One comes from convergence considerations of the adapted PCLMN [3] that resemble the convergence of a class of neural network known as the Andersen Brain-State-In-a-Box network [4] and the second comes from extensive numerical simulations in which the adapted PCLMN was probed by 100 distinct dynamic (spatio-temporal) input patterns, and by examining the histogram of the Euclidean distances between their convergent states (attractors).

Other significant properties of the adapted PCLMN are: (a) ability to represent both dynamic or static input (stimulus) patterns by fixed-point attractors, (b) rapid convergence to an attractor occurring within few tens of iterations (time steps) in numerical simulations, (c) ability to differentiate redundant (structured) inputs from nonredundant or unstructured inputs that are void of information and, (d) the nearest-neighbor connections architecture facilitates analog VLSI implementations of the PCLMN.

Numerical Simulations

An example of the numerical simulation of the PCLMN is presented next in Figures 1 and 1(c). The central top plots in Fig. 1 show two snapshots of the time evolution of the state-vector $\overline{X}(n)$ of a PCLMN of N = 100 processing elements. The narrow leftmost window mus on the top left shows the values of the control vector

$\overline{\mu}$ of a stimulus generating layer of individual logistic maps producing a dynamic (spatio-temporal) input vector $\overline{X}^s(n)$ a snipet of which is shown to mus the window. The right-most narrow window gives the encoding scale of the orbits $0 \le X_i(n) \le 1$ of the individual elements of the network, while SZ is the spatial power spectrum of $e^{j2\pi X_i(n)}$ where $X_i(n)$ is regarded as normalized phase variable. The next two panels from the top show the time evolution of $X_i(n)$ for the $i=0$ element. The bottom square pattern is the mutual information matrix computed at the 499-th iteration from the preceding 100 iteration. Without adaptation the nature of the steady-state pattern $\overline{X}(n)$ of the network shown for $400 \le n \le 499$ would persist and so would the mutual information matrix. The top left entry in Figure 1(b) shows the state variable $\overline{X}(n)$ of the network following the first MI (mutual information) driven adaptation of the initial coupling factors matrix $\overline{C}(0)$ executed at the 400 iteration together with the MI matrix computed from $\overline{X}(n)$, $400 \le n \le 499$ which is shown at the top right. The bottom entries in Fig. 1(b) show the convergent $\overline{X}^*$ (left) reached after four MI driven adaptations of the network made at $n = 400, 500, 600, \text{and } 700$ using always the preceding 100 iterations of the network. The corresponding MI matrix is given at the bottom right showing its elements I_{ij} have conveyed to zero. Because I_{ij} is a measure of the flow of information between the i-th and j-th elements, convergence of the network is synonymous with a convergent $\overline{C}$ matrix that eliminates the flow of information between the elements (PCLMs) of the network. We call this process *MI driven self-organization*. In the convergent state all elements have converged to fixed analog values ranging between zero to a maximum value determined by the upper limit of the fixed-point regime of the bifurcation diagram of the conventional (undriven) logistic map which is normalized to 1. Figure 1(c) shows the convergent state vector $\overline{X}^*$ or fixed-point attractor reached by the network for a different distinct input pattern $\overline{X}^s(n)$ and the associated zero MI matrix. Note also the spatial convergence of the power spectrum $\overline{\text{SZ}}$ and its resemblance then to an analog bar-code which can be used to label the convergent attractors.

In the preceding simulation each applied input selects one of the $N = L^N$ fixed-point attractors of the network. The selection takes place via a process of conjugation of the input with the dynamics of the network. This process defines a new concept: that of a *dynamic memory* with an enormous built-in capacity. The network is able to produce an *internal representation*, a fixed-point attractor, for every input it receives. The labeling of internal representations by means of a suitable associative memory or a lookup table e.g., a bar-code reader of the convergent $\overline{\text{SZ}}^*$ can be used to impart meaning to the representations/attractors forming thereby what can be called as a *cortical module* that can be used in automated input/object recognition.

The PCLMN has another mode of operation that speeds-up the convergence to a fixed-point attractor. This involves *commulative adaptation* of the network by several distinct input patterns that leads to a commulatively MI driven self-organized network capable of converging to an attractor in approximately 50 iterations instead of the 800 or 900 iterations needed to converge in Fig. 1. In this commulative adaptation process the final convergent $\overline{C}$ matrix arrived at as result of applying a first input to the unadapted network with $\overline{C}(0)$ is used as the initial $\overline{C}(0)$ for a second distinct input applied to the network and the new convergent $\overline{C}$ matrix is used as $\overline{C}(0)$ for a third distinct applied input and the process is repeated. Normally a total of three or four distinct inputs was sufficient to make the values in the $\overline{C}$ matrix stabilize and not change with further application of distinct inputs. Such commulatively self-organized network has the remarkable property of being able to distinguish between redundant (structured) and non-redundant (unstructured) inputs where the latter consists of random spatio-temporal patterns that contain no meaningful information.

Conclusions

MI driven self-organization in a parametrically coupled logistic map network capable of handling dynamic or static input and representing them by input-specific fixed-point attractors was described. The network acts as dynamic memory capable of furnishing an enormous number of attractors the input can choose from. Commulative adaptation of the network starting from a suitably formed random activity-dependent coupling matrix that spawns initial disorganized activity leads to rapid convergence as compared to the noncommulatively adapted network where the initial coupling matrix for all applied inputs is the same. The commulatively adapted or self-organized network has several intriguing properties one of which is the ability to differentiate between redundant and non-redundant inputs which is a well known property of the brain.

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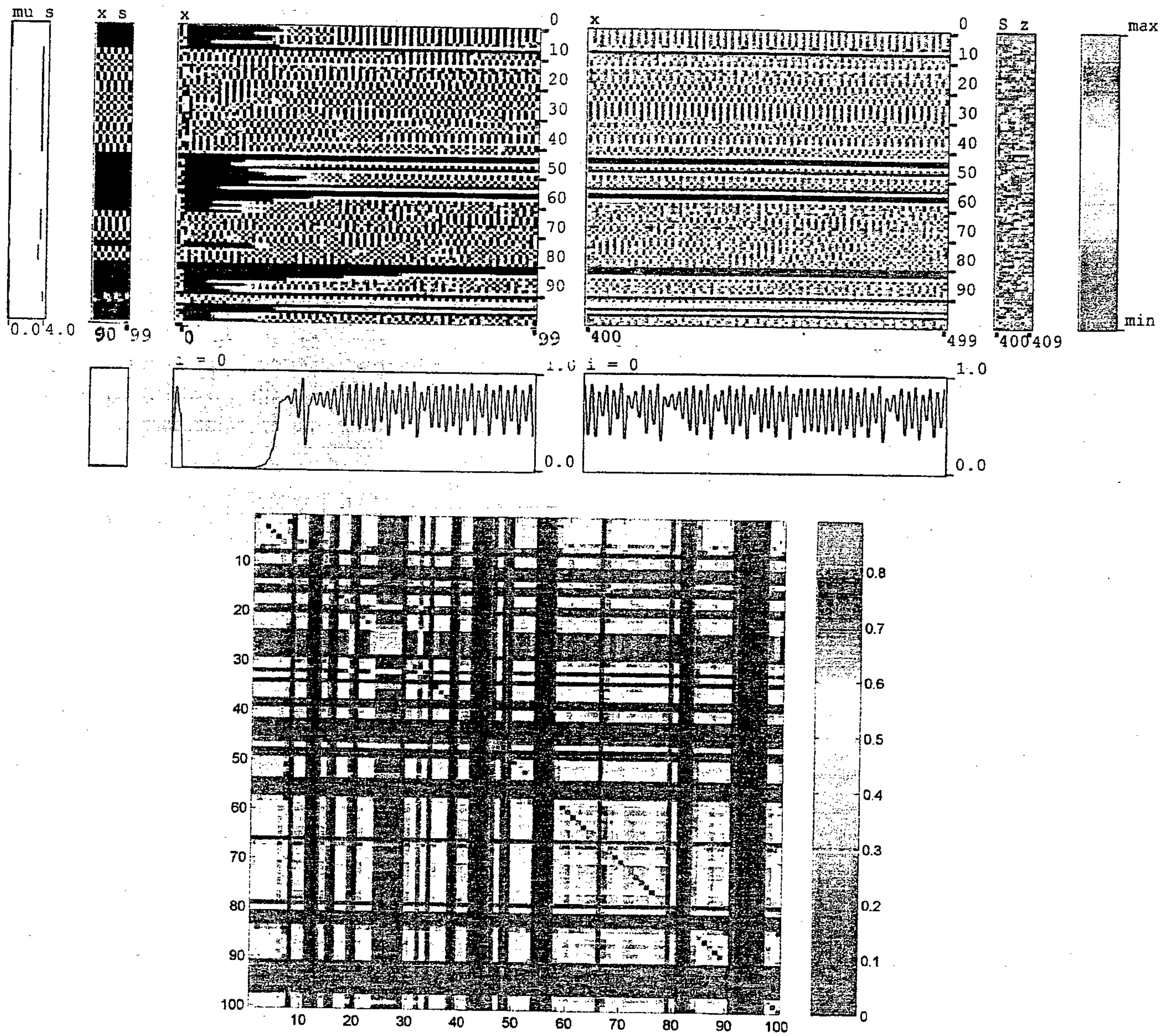

Fig. 1(a). Input-specific orbits (top) and mutual information matrix (bottom) without MI driven adaptation of the network.

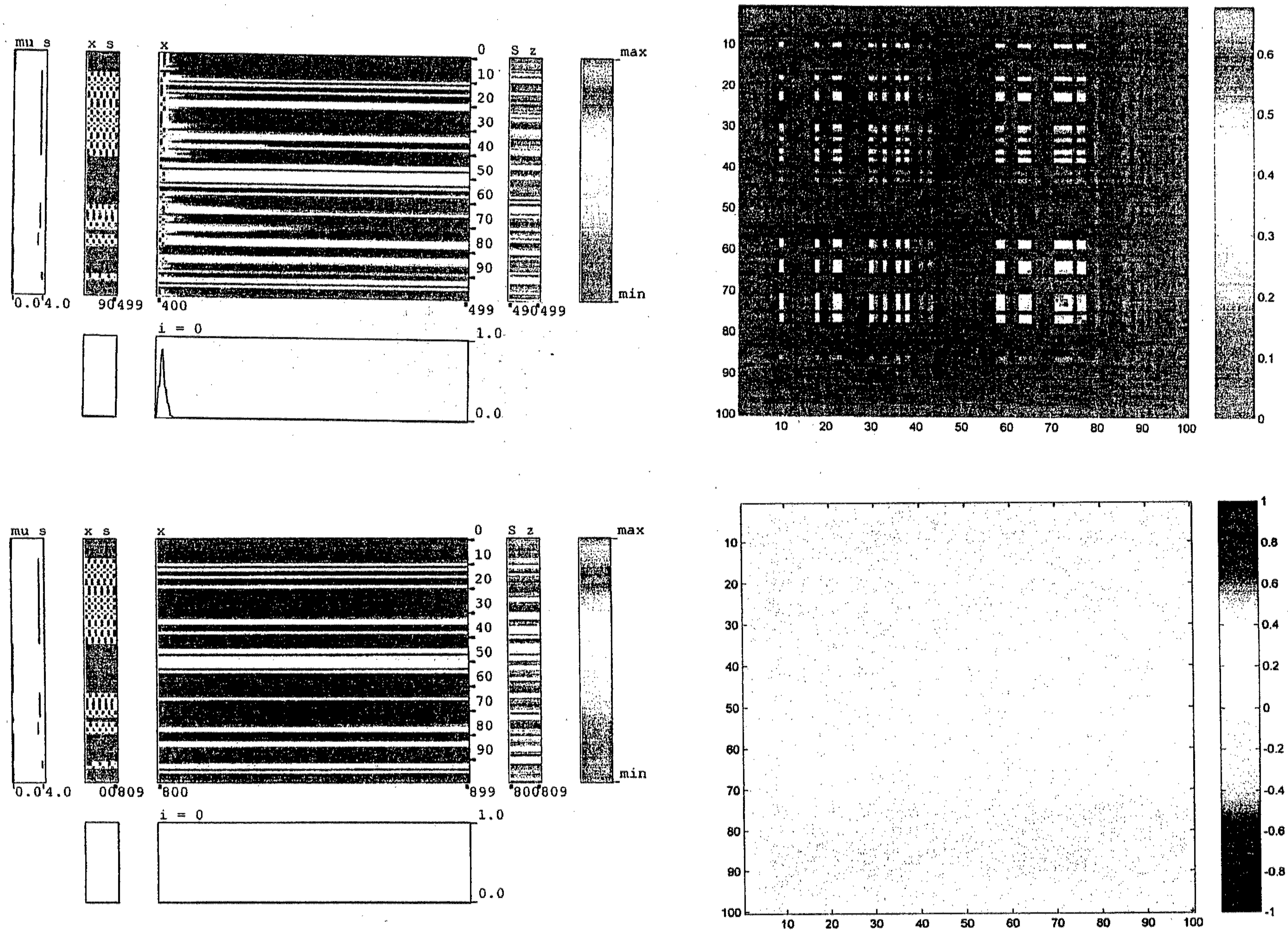

Fig. 1(b). (Top) Orbits and MI matrix following first adaptation. (Bottom) Fixed-point attractor and MI matrix showing flow of information in convergent network is zero.

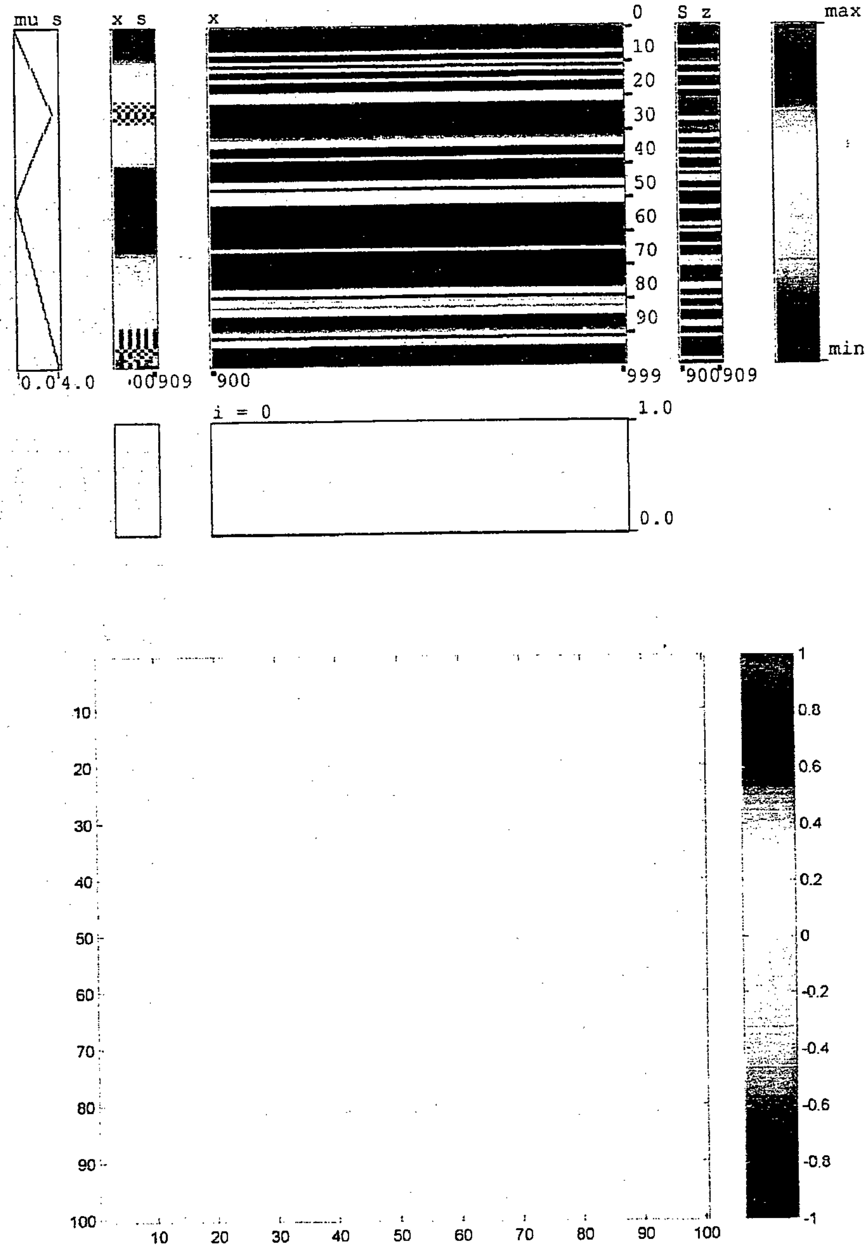

Fig. 1(c). Another input-specific attractor and MI matrix. Note different inut pattern $\overline{X}^{s}$.